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Ansgar Belke • Christian Gokus

**Volatility Patterns of CDS, Bond and Stock  
Markets before and during the Financial Crisis  
Evidence from Major Financial Institutions**

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## IMPRESSUM

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DIW Berlin  
German Institute for Economic Research  
Mohrenstr. 58  
10117 Berlin

Tel. +49 (30) 897 89-0  
Fax +49 (30) 897 89-200  
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# **Volatility patterns of CDS, bond and stock markets before and during the financial crisis:**

## **Evidence from major financial institutions**

**Ansgar Belke**

(University of Duisburg-Essen, DIW Berlin and IZA Bonn)

**and**

**Christian Gokus**

(University of Duisburg-Essen, Germany)

Berlin and Essen

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### **Abstract**

This study is motivated by the development of credit-related instruments and signals of stock price movements of large banks during the recent financial crisis. What is common to most of the empirical studies in this field is that they concentrate on modeling the conditional mean. However, financial time series exhibit certain stylized features such as volatility clustering. But very few studies dealing with credit default swaps account for the characteristics of the variances. Our aim is to address this issue and to gain insights on the volatility patterns of CDS spreads, bond yield spreads and stock prices. A generalized autoregressive conditional heteroscedasticity (GARCH) model is applied to the data of four large US banks over the period ranging from January 01, 2006, to December 31, 2009. More specifically, a multivariate GARCH approach fits the data very well and also accounts for the dependency structure of the variables under consideration. With the commonly known shortcomings of credit ratings, the demand for market-based indicators has risen as they can help to assess the creditworthiness of debtors more reliably. The obtained findings suggest that volatility takes a significant higher level in times of crisis. This is particularly evident in the variances of stock returns and CDS spread changes. Furthermore, correlations and covariances are time-varying and also increased in absolute values after the outbreak of the crisis, indicating stronger dependency among the examined variables. Specific events which have a huge impact on the financial markets as a whole (e.g. the collapse of Lehman Brothers) are also visible in the (co)variances and correlations as strong movements in the respective series.

*Keywords:* bond markets, credit default swaps, credit risk, financial crisis, GARCH, stock markets, volatility

*JEL classification:* C53, G01, G21, G24

*Corresponding author:* Ansgar Belke, DIW Berlin and Chair for Macroeconomics, University of Duisburg-Essen, Campus Essen, Department of Economics, 45117 Essen, Germany; phone: (0049)-201-1832277, fax: (0049)-201-1834181, e-mail: [ansgar.belke@uni-due.de](mailto:ansgar.belke@uni-due.de).

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# 1. Introduction

The financial crisis that unfolded in summer 2007 has had a huge impact on a number of financial institutions in the United States and Europe. The market turmoil severely affected especially those internationally active banks with large exposures to mortgage-related asset-backed securities (ABSs) or collateralized debt obligations (CDOs). All banks had to deal with an uncertain and more volatile market environment resulting in severely impaired overall performances. Consequently, concerns about the solvency of some large US and European financial institutions arose.

Investors as well as central banks and supervisory authorities are in need of market-based indicators to assess the soundness of the banking sector, since bank failures can have devastating effects on the economy. That was especially apparent after the collapse of Lehman Brothers in September 2008 which has pushed the global financial system to the brink of systemic meltdown. Market participants are aware of rating agencies being too slow to provide a proper risk assessment of companies. When facing increased risk in financial institutions the question arises how the market can figure out changing risk profiles of these institutions. A very straightforward approach is to gain important information by monitoring prices of bank securities. This price information provides a good yardstick for how market participants assess the risk of financial institutions (Persson, Blavarg 2003, p. 5). Accordingly, our paper is motivated by the development of credit-related instruments and signals of stock price movements of large banks during the financial crisis.

The empirical literature has identified three major variables which are closely linked with the performance of a firm (see for instance Norden, Weber 2009; Forte, Peña 2009). The most prominent market indicators are probably the traditional instruments like stock prices and bond yield spreads. Over the recent years, the market for credit default swaps (CDS) has received special attention, as CDS should reflect pure credit risk of borrowers. The relationship between those variables has been subject to many empirical studies with the result that in particular the stock and the CDS market can quickly process credit-related information. For example Hull, White and Predescu (2004) show that CDS can even anticipate rating agency changes.

What is common to most of these studies is that they concentrate on modeling the conditional mean. Generally, financial time series exhibit certain stylized features such as volatility clustering and high kurtosis. In this paper we address this issue empirically to gain deeper insights on the volatility patterns of CDS spreads, bond yield spreads and stock prices. For

this purpose, we apply a generalized autoregressive conditional heteroscedasticity (GARCH) model to the data of four large US banks over the period from January 1, 2006, to December 31, 2009. More specifically, we conduct a multivariate GARCH approach to also account for the dependency structure of the variables under consideration. Our empirical analysis provides evidence of strongly time-varying conditional covariances and correlations between the market-implied risk indicators and that the empirical realizations of these measures have been exhibiting a substantially higher level during the financial crisis. This is especially true for the variances of the examined variables. Overall, the latter increase synchronously around specific events with a huge impact on financial markets such as, for example, the collapse of Lehman Brothers. However, the bond yield spread variances exhibit a slightly different pattern. An increased correlation in the course of the crisis could also be observed among the CDS spreads of the different banks.

Since volatility is often regarded as a measure of risk, the investigation of the second moments of the market implied risk indicators could provide additional information on the financial condition of the examined institutions as well as the financial system as a whole.

We organize the remainder of our paper as follows. In section 2 we develop some arguments why rating agencies might not be preferred by market participants as an early indicator of risk. In section 3 we present the theoretical background and the characteristics of certain market prices which are identified in the literature as important providers of information concerning a firm's soundness. Moreover, we explain why they may be preferred to credit rating information. Since the aim of our empirical analysis is to examine the volatility patterns of the identified variables, we present some literature on this issue in section 4 in conjunction with some hypotheses to be tested later on. In section 5 we report the results of a detailed empirical investigation of the volatility patterns of the risk indicators which also includes the dependency structure. Evidence is provided for specific commercial banks using a multivariate GARCH approach. Section 6 concludes and summarizes our main results.

## **2. Rating agencies and the need for market-based indicators**

The recent financial crisis which started in summer 2007 has highlighted that the accurate and timely evaluation of credit risk in companies, especially in large banks, is of utmost importance to avoid severe disruptions in the affected sectors. In particular, the bankruptcy of Lehman Brothers in September 2008 unfolded the consequences if the credit risk of large global financial players cannot be detected early enough.

Over the course of the financial crisis, the questionable behavior of rating agencies became an issue of high importance in public discussions. In general, credit ratings provide information on the relative creditworthiness of issuers as well as their issued debt. Although default risk cannot be measured precisely, the standardized risk categories make it possible to compare issuers (Micu, Remolona, Wooldridge 2004, p. 55f.).

The information provided by credit rating agencies are considered as an important input for the decision-making of investors in credit markets and serve as a fundamental input to different kinds of credit risk models (for instance the pricing model of Jarrow, Lando, Turnbull 1997). Pension funds and other institutional investors rely heavily on the assessment of credit risk, as they are legally bound to hold only investment grade bonds. Therefore, various market participants are concerned about changes in credit ratings, since they can raise the capital costs of issuers, influence credit spreads and bond returns as well as the prices of credit derivatives (Kou, Varotto 2005, p. 2f.).

Although rating agencies play a very important role in the economy, they often reveal some shortcomings in the timely and accurate assessment of debtors' credit risk. One problem is the weak performance of credit ratings as an early indicator of potential risk. Another critical issue is the potential conflict of interest. This problem arises due to the fact that debtors pay the agencies to evaluate their debt. Especially during the subprime crisis starting in mid-2007 the validity of credit ratings were questioned by market participants. The rating agencies have come under scrutiny and were seen as one possible cause in the mispricing of credit risk. Concerns arose that due to the inability to rate mortgage credit properly, this inability could spill over to other credit markets (Jacobs, Karagozoglu, Peluso 2010, p. 2f.). Following the subprime debacle, risk aversion increased as well as the uncertainty about credit products (e.g. bonds and CDS) regardless of their actual credit rating or the perceived creditworthiness with the consequence that borrowers had to pay a higher compensation to potential investors for bearing default risk (Jacobs, Karagozoglu, Peluso 2010, p. 2f.).

Due to the above mentioned shortcomings of credit ratings, the demand for market-based indicators has risen, as they can help to assess the creditworthiness of debtors more reliable. Market-based indicators can potentially react immediately to macroeconomic or company related news, whereas rating agencies need some time to process new information (Di Cesare 2006, p. 122). The usefulness of market information for policy purposes has already been acknowledged. For instance, the term structure of interest rates or implied volatilities have

been used in the decision-making process of monetary policy and supervisory authorities (Annaert et al. 2010, p. 1).

Daniels and Jensen (2005) find that the bond and the CDS market can anticipate credit rating changes (downgrades better than upgrades). Furthermore, in this respect the CDS market reacts faster than the bond market (Daniels, Jensen 2005, p. 31). These results confirm the findings by Hull, Predescu and White (2004, p. 2800ff.) who also underline the ability of CDS spreads to anticipate rating announcements. Analyzing the informational content of the stock and CDS market, Norden and Weber (2004, p. 2837f.) show that both markets anticipate rating changes.<sup>1</sup> Market prices of traded instruments can also be used to derive “synthetic” ratings for credit risk (see, for instance, Varotto and Kou 2005).

Particularly, in the course of the financial crisis, supervisory authorities relied on the information content of market variables to get a timely indication of financial stress in the banking sector. Lately, credit spreads on single-name obligations have been monitored more closely and have gained more importance as a supervisory instrument. Especially credit default swap spreads are perceived as a measure of pure credit risk which may serve as a benchmark for measuring and pricing credit risk and may suit the needs of a credit risk proxy better than corporate bonds (Abid, Naifar 2006, p. 40; Norden, Weber 2009, p. 530). CDS are related to the creditworthiness of a firm or sovereign and make it possible to efficiently hedge and separate credit risk from the underlying credit relationship (Deutsche Bundesbank 2004, p. 44). Hence, CDS spreads may detect possible defaults or credit events of firms more accurately and earlier. By now, CDS spreads are the most prominent market-based indicator of credit risk. This development is justified by the rapidly growing market for credit default swaps (Annaert et al., p. 1f.). Nevertheless, bond spreads and equity prices should not be neglected in the analysis of credit risk. Stocks, like bonds, are claims on a firm and therefore default risk should be reflected by market prices on these claims. They can potentially contribute to the detection of risk, since those markets process information much faster than credit rating agencies.

### **3. Linking bond spreads to CDS spreads and stock prices**

Movements in corporate bond spreads reflect market expectations of how the credit outlook of firms will be in the future. The spreads are usually calculated as the difference between the risky corporate bond yields and the yields on government bonds or swap yields which are

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<sup>1</sup> For further information on the relationship between credit rating related information and CDS spreads in European capital markets see, for instance, Lehnert and Neske (2006).



proxies for the risk-free interest rate.<sup>2</sup> Thus, the spreads on corporate bonds are the risk premium corporations have to pay the investors as a compensation for several risks inherent in corporate debt, for instance, default risk, liquidity risk and prepayment risk (Alexopoulou, Andersson, Georgescu 2009, p. 1).

A theoretical relationship between CDS and bond spreads can be derived from the so-called reduced-form models.<sup>3</sup> The equality relationship between both spreads can easily be established by means of the risk neutral default probability as well as no-arbitrage conditions. The underlying reasoning has been proposed by Duffie (1999) and Hull and White (2000). In this case, the risk-free interest rate is constant over time. Buying a CDS for protection purposes requires a payment of a constant premium until a default occurs (or any other predefined credit event) or the contract matures. If the firm defaults, the protection seller has to pay the difference between the face value and the market value of the reference obligation.

Considering the no-arbitrage conditions, it is possible to replicate the credit default swap synthetically by shorting a bond with fixed coupon at par on the same reference entity with the same maturity date. The returns should then be invested in a par risk-free note with fixed coupon. As a result, the CDS premium and the par bond with fixed coupon should be equal. Deviations from this parity enable to make arbitrage profits (Zhu 2006, p. 214).

Nevertheless, various reasons may hinder the parity relationship to hold in practice. The deviation from the equivalence of CDS and bond spreads can be explained by the failure of some of the underlying assumptions in reality, e.g. non-constancy of the risk-free interest rate.

The considerations above illustrate the close relationship between CDS and bond spreads if certain restrictive assumptions are satisfied. Nevertheless, some advantages of CDS spreads in comparison to bond spreads can be identified (Anneart et al. 2010, p. 2). Bond spreads are calculated as the difference between risky bonds and a risk-free interest rate, i.e. they have to be computed first and cannot be observed directly, in contrast to CDS spreads. Moreover, the identification of the credit premium in the spreads of risky bonds is probably contaminated by liquidity (Chen, Lesmond and Wei 2007, p. 121), tax effects (Elton et al. 2001, p. 248) and microstructure effects.

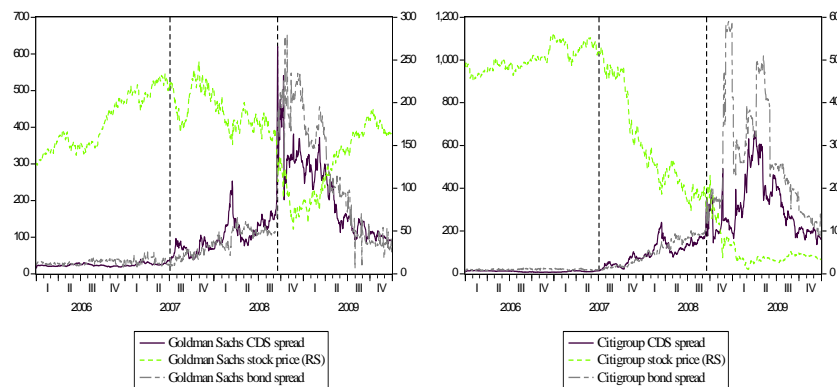
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<sup>2</sup> The swap zero curve is usually used by derivative traders considering Libor/swap rates as the opportunity cost of capital.

<sup>3</sup> Two major groups of credit risk models are mostly used in the analysis of credit risk pricing. In structural models, default risk is handled as an endogenous process, partially accounted for by the structural factors, in contrast to reduced-form models where a firm's default cannot be anticipated and is determined by an exogenous default intensity process (Alexopoulou, Andersson, Georgescu 2009, p. 9).

The equity market is regarded as a very important provider of information for a firm's soundness. To illustrate how bond and equity prices are related, Merton (1974) proposes a theoretical framework which makes use of the option-pricing theory. The model shows that equity prices and bond spreads are highly connected and should move in opposite directions. To draw a connection to the CDS market, the close relationship of bond and CDS spreads suggests that credit default swap spreads and equity prices should also disperse (Chan-Lau, Kim 2004, p. 8f). Looking at two major banks such as Goldman Sachs and Citigroup, it becomes obvious from the data that the spreads and stock prices move in opposite directions (see Figure 1).

**Figure 1: CDS spreads, bond spreads and stock prices of selected financial institutions**



Data source: Thomson Reuters Datastream.

Note: Bond spreads are spreads over the swap curve with 5 year maturity. Bond spreads and CDS spreads are denoted on the left axis in bp; for stock prices refer to the right scale (RS) in US dollar. Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers).

#### 4. Related literature and derived hypotheses

Financial time series exhibit certain stylized features such as volatility clustering or time-varying correlations which cannot be grasped sufficiently by models based on the assumption of homoscedasticity (Schreiber et al. 2009, p. 3). Very few studies dealing with credit default swaps account for the characteristics in the variances. Correlations within the market for credit default swaps are also a very important aspect for market participants and supervisory authorities, as increasing correlations are often referred to contagion (Coudert and Gex 2008).

Scheicher (2009) analyzes conditional correlations between stock returns and changes in CDS premia for a sample of 240 firms covering the years 2003-2005. The author shows in a bivariate EWMA framework that periods of market turbulence lead to strong increases in these correlations and that correlations among individual firms are substantially volatile. An overall negative correlation between CDS spread changes and equity returns can be observed

without considerable differences between US and European samples. The time-varying negative correlation does also hold for investment grade and high-yield segments of the credit market. The finding of a negative correlation supports the findings by Norden and Weber (2009) as well as a study by Kwan (1996) who also documents a significant negative relation between stock prices and corporate debt (Scheicher 2009, p. 416).

Schreiber et al. (2009) fit two different VAR-GARCH approaches (BEKK and DCC parameterization) and investigate the conditional covariance structure by using daily data of the iTraxx Europe, Euro Stoxx 50 and VStoxx index over the period June 2004 to April 2009 (Schreiber et al. 2009, p. 2). They detect a strong variation over time in the conditional variances and correlations. In particular, the authors find the correlations between the iTraxx and the Euro Stoxx, and the Euro Stoxx and the VStoxx to be negative. A positive correlation exists between the iTraxx and the VStoxx. In addition, a significant increase in the absolute values of the correlations can be observed after the start of the subprime crisis (Schreiber et al. 2009, p. 20).

Meng, ap Gwilym and Varas (2009) are interested in the volatility transmission among the bond, CDS and equity. Their study should help to shed light on the efficiency of the respective markets. The authors use return data of the three variables for ten large US companies in a multivariate GARCH (BEKK) approach over the period 2003-2005. They find little support for the hypothesis that the CDS market is the originator of volatility transmission to the equity and bond market. Rather, they confirm that the link between the markets has strengthened. The almost reciprocal volatility spillover supports the view that innovations in one market can influence the other markets as investors are in search for high yield across different assets. Accordingly, shocks originating in one market can cause increased trading activity in the two other markets. Therefore, regulators should keep in mind the strong linkage between the CDS, bond and equity markets (Meng, ap Gwilym, Varas 2009, p. 44f.).

The empirical literature dealing with volatility patterns of the CDS, bond and equity markets disclose that certain characteristics can be observed regarding the correlations and (co)variances over time. All studies reveal that the conditional (co)variances for the different variables are strongly time-varying and especially in turbulent times are on a much higher level (cf. Schreiber et al. 2009, p. 14f.). The same pattern could be observed for the conditional correlations between the CDS and stock market, and the bond and stock market. This suggests that the correlations are not overall constant over time and should become more

pronounced during the period after the start of the subprime crisis. Accordingly, our hypothesis one runs as follows:

*H1: The conditional (co)variances vary over time with correlations taking higher levels during the crisis period.*

Furthermore, the obvious structural break in the original series (see Figure 1) should also be present in the conditional (co)variances. As stated by Coudert and Gex (2008, p. 13), volatility will generally increase in times of crisis which is supported by other studies (cf. Scheicher 2009; Schreiber et al. 2009). Especially around the date of the collapse of Lehman Brothers, strong movements should be visible in the covariances and variances. Coudert and Gex (2008, p. 13f.) even use volatility patterns in the CDS market to identify the start of a crisis period (in this case the GM and Ford crisis in 2005). Since CDS spreads, stock prices and bond yield spreads should fundamentally represent the financial condition of a company, events affecting the financial outlook of the firm should also be observed in the volatility of all three variables.

*H2: Variances and covariances of CDS spreads, bond yield spreads and stock prices move in a similar fashion due to credit-related events affecting a company.*

Actually, a co-movement of volatilities may hint at the fact that the different markets are affected by the same economic shock.

In the recent past, the market for credit default swaps has received special attention in the analysis of credit risk. CDS spreads are widely regarded as an important indicator of potential default risk and, what is more, CDS spreads may be used as a complement to credit ratings. Credit default swap premia increased dramatically in the course of the financial crisis. As Rhaman (2009) and Coudert and Gex (2008) persuasively reassure, the correlations between CDS spreads of different institutions should also increase in turbulent times which may indicate contagion effects.

*H3: Correlations between CDS spreads of different companies increase with the start of the financial crisis.*

## **5. Empirical analysis**

### **5.1 Data**

For our empirical analysis, we have collected data for CDS spreads, bond yields, and equity prices of four large US financial institutions: Bear Stearns, Citigroup, Goldman Sachs and

Merrill Lynch. Hence, our sample contains banks which were under severe distress during the financial crisis. Especially Bear Stearns and Merrill Lynch had been hit very badly by the crisis and were then taken over by other large banks. These institutions have been chosen because of their importance in the financial markets due to their (former) large market power.

The whole sample period covers the years from January 2006 to December 2009, including more than 1,000 observations (if the time series is not discontinued due to takeovers like in the case of Bear Stearns and Merrill Lynch). The whole period is characterized by a tranquil phase (pre-crisis period) at the beginning of the sample period (January 1, 2006, to mid-2007) in which the CDS and the bond spreads maintained a rather low level and stock prices were still on a high level. The second phase is characterized by high volatility and uncertainty after mid-2007 (crisis period).

The data for credit default swaps consists of daily mid-CDS spreads for the reference entities expressed in basis points (bp). Senior debt CDS with a maturity of 5 years have been chosen, since they are the most liquid maturity segment. CMA (Credit Market Analysis) quotes were retrieved from Thomson Reuters Datastream.<sup>4</sup>

One problem which arises when comparing 5-year CDS spreads and bond yield spreads is the fact that it is nearly impossible to find a corporate bond which matches the 5-year constant maturity of the CDS contracts. In order to solve this problem, a synthetic bond has to be constructed following the methodology of Blanco, Brennan and Marsh (2005, p. 2260), and Norden and Weber (2009, p. 534).<sup>5</sup> To build the 5-year risky corporate bond, the daily yields (redemption yields) of two bonds were linearly interpolated. For this purpose, one bond with 3 to 5 years left to maturity at the beginning of the sample period and one bond with more than 5 years to maturity also at the start of the sample has been used. All bonds are straight bonds with fixed coupons, and only bonds in the currency of the CDS were considered.

The bond yield spreads can be calculated by subtracting the risk-free interest rate from the synthetic 5-year constant bonds. As noted by Hull, Predescu and White (2004, p. 2795f.) and Houveling and Vorst (2005, p. 1223), government bonds, which are usually used, may not be the appropriate benchmark rate. For example, investors in the derivative market generally rely on the swap curve in their decisions (Blanco, Brennan, Marsh 2005, p. 2261).<sup>6</sup> These data

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<sup>4</sup> CMA provides independent and accurate OTC market data (see <http://www.cmavision.com>).

<sup>5</sup> Similar procedures are conducted by, for instance, Longstaff, Mithal and Neis (2005, p. 2222ff.) and Zhu (2006, p. 216ff.).

<sup>6</sup> The appropriate data for the bond yield spreads as well as the equity prices were retrieved via Thomson Reuters Datastream for all entities.

were then used to construct the generic spread to match the 5-year maturity. All series are denominated in US Dollars and applied in log-differences in order to obtain stationarity. The time series patterns resemble a GARCH process.<sup>7</sup>

## 5.2 Modeling volatility with GARCH

Engle (1982) demonstrates that the typical characteristics of financial time series can be modelled, using an autoregressive conditional heteroscedasticity (ARCH) model which is extended by Bollerslev (1986) to its generalized version (GARCH). In order to capture the simultaneous volatility clustering and to gain important insights into the co-movement of financial time series, univariate GARCH models have been extended to the multivariate case (for an extensive survey on multivariate GARCH models see Silvennoinen, Teräsvirta 2009 or Bauwens, Laurent, Rombouts 2006). Modeling the conditional covariance structure is especially important in asset pricing, risk management and can also help to analyze volatility and correlation spillover and transmission effects (Silvennoinen, Teräsvirta 2009, p. 202). In addition, the strong linkage of the CDS, bond and equity market described above makes it reasonable to use a multivariate GARCH framework for the analysis of the volatility patterns.

The specification of multivariate GARCH models (MGARCH) should be parsimonious to guarantee a relatively easy estimation and interpretation of the parameters, as a higher dimension of the MGARCH model leads to a rapidly increasing number of parameters to be estimated. Another important aspect is the positive definiteness of the covariance-variance matrix which should be guaranteed, as this matrices need by definition to be positive definite (Silvennoinen, Teräsvirta 2009, p. 203).

Since the main focus lies on the time-varying covariance structure, the mean equation is usually specified simply as a constant or a low-order autoregressive moving average (ARMA) process to capture autocorrelation caused by microstructure or non-trading effects (Zivot 2009, p. 118). The model structure can be described as follows:

$$r_t = \mu_t + \varepsilon_t \quad (1)$$

$$\varepsilon_t = H_t^{1/2} v_t, \quad v_t = i.i.d. \quad (2)$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, H_t) \quad (3)$$

where  $r_t$  represents a vector of returns (e.g. stock, CDS and bond returns), whereas  $\mu$  is a  $N \times 1$  vector and contains the parameters that estimate the mean of the return series. The

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<sup>7</sup> Due to space limitations, results of stationarity tests as well as a preliminary data analysis are not reported and are available on request.

vector  $\varepsilon_t$  equals the residuals with the corresponding conditional covariance matrix  $H_t$ , given the available information set  $\Omega_{t-1}$ .  $v_t$  is a white noise error term. The multivariate form of the GARCH model requires the specification of the covariance matrix  $H_t$ .

For this purpose, Engle and Kroner (1995) define the BEKK (Baba-Engle-Kraft-Kroner) model. This model reduces the number of parameters to be estimated compared to other multivariate GARCH specifications and especially the positive definiteness of the conditional covariance matrix is guaranteed by construction (Baur 2006, p. 7; Silvennoinen, Teräsvirta 2009, p. 205). The unrestricted first order BEKK-GARCH(1,1) model may be written as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (4)$$

where  $C$ ,  $A$  and  $B$  are  $N \times N$  parameter matrices, and  $C$  is upper triangular (Tsay 2006, p. 212). One can easily see from equation (4) that  $H_t$  is positive definite as long as the diagonal elements of  $C$  are positive. This is due to the quadratic formulation of the conditional variance equation. Although the BEKK model contains fewer parameters than e.g. the VEC model, their number still remains high. A further simplification can be achieved by restricting the matrices  $A$  and  $B$  to be diagonal which will be used in the following.

The conditional variances  $(h_{11,t}, h_{22,t}, h_{33,t})$  depend on the lagged squared conditional variances and lagged squared errors, whereas the covariances  $(h_{21,t}, h_{31,t}, h_{32,t})$  depend on the cross-products of the lagged conditional variances and errors, respectively. The interpretation of the parameters is not clear-cut. It is obvious that no parameter in any equation exclusively governs a particular covariance equation. Hence, it is difficult to identify whether the parameters for  $h_{21}$  are just the result of the parameter estimates for  $h_{11}$  and  $h_{22}$  or whether the covariance equation alters the parameter estimates of the variance equations. The parsimonious representation of the diagonal BEKK model comes at the cost of flexibility (Baur 2006, p. 8). Whereas for the empirical work, the BEKK model is in most cases superior to the VEC model, since the estimation is much easier due to the reduced number of parameters (Soriano, Clement 2006, p. 37).

### 5.3 Estimation and results

The parameters of the multivariate GARCH specification are estimated by maximizing a log-likelihood function assuming conditional normality and using the BHHH (Berndt, Hall, Hall, Hausmann 1974) algorithm. Although the excess kurtosis inherent in the returns series would

suggest a Student's t-distribution for the estimation to account for the fat tails, financial time series are often skewed and therefore the application of a Student's t distribution may be questioned (Schreiber et al. 2009, p. 16f.).

To keep the model simple, the return series in most multivariate GARCH applications are regressed only on a constant (see for instance Kearney and Patton 2000) or optionally on additional AR terms to account for the autocorrelation patterns in the series (e.g. Darbar and Deb, 1997). The subsequent empirical analysis makes use of an AR(1) model plus constant for the conditional mean. It appears to be an adequate representation of the mean in order to account for the autocorrelation which is partly existent in the time series and should guarantee appropriate estimates for the conditional (co)variances.

The mean equations for the returns on stocks (*st*), CDS spreads (*cds*) and bond yield spreads (*bo*) can be written as follows:

$$r_{it} = \omega_{it} + \phi_{it} r_{it-1} + \varepsilon_{it} \quad (5)$$

Where  $r_{it}$  is the return of series  $i$  at time  $t$  and  $\omega_{it}$  denotes the constant of series  $i$  ( $i = 1, 2, 3$  with  $1 = st$ ;  $2 = cds$ ;  $3 = bo$ ).  $\phi$  measures the influence of  $r_{it-1}$  and  $\varepsilon_{it}$  is the error term of the respective series. The error process follows equation (4) where  $\varepsilon_t$  is:

$$\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix} \quad (6)$$

The usual model selection criteria, such as the Akaike (AIC) and Schwarz (SIC) information criteria as well as the value of the maximized likelihood function were used to test for the appropriate model order. Table 1 contains the results of different specifications for the diagonal BEKK model.

The AIC and SIC criterion as well as the ML value indicate that a BEKK(1,2) or a BEKK(2,1) specification would be appropriate to model the volatility patterns of the return series. However, adding additional ARCH or GARCH terms to the specification improves the model only slightly, especially when comparing AIC and SIC of the different models. Furthermore, many researchers dealing with financial time series have shown that GARCH(1,1) specifications often proved to be sufficient to yield efficient and significant results (see for instance Bollerslev, Chou, Kroner 1992). Hansen and Lunde (2005, p. 887) even note that it is difficult to outperform the simple GARCH(1,1) model. Therefore, the



model order was deliberately held simple and the following estimation results were obtained from the estimation of a diagonal BEKK(1,1) specification.

**Table 1: Model order selection for AR(1)-BEKK( $p,q$ ) for  $p, q = 1,2$**

	Criterion	BEKK(1,1)	BEKK(1,2)	BEKK(2,1)	BEKK(2,2)
<b>Bear Stearns</b>	<b>AIC</b>	-8.752	-8.922	-8.401	-8.451
	<b>SIC</b>	-8.624	-8.773	-8.252	-8.281
	<b>ML</b>	2770.391	2826.927	2663.044	2681.817
<b>Citi-group</b>	<b>AIC</b>	-9.135	-9.144	-9.141	-9.047
	<b>SIC</b>	-9.050	-9.044	-9.041	-8.933
	<b>ML</b>	4781.962	4789.646	4787.893	4741.782
<b>Goldman Sachs</b>	<b>AIC</b>	-8.873	-8.920	-8.894	-8.744
	<b>SIC</b>	-8.788	-8.820	-8.794	-8.631
	<b>ML</b>	4645.488	4672.771	4659.136	4584.209
<b>Merrill Lynch</b>	<b>AIC</b>	-9.375	-9.447	-9.431	-9.308
	<b>SIC</b>	-9.268	-9.322	-9.306	-9.165
	<b>ML</b>	3683.788	3714.795	3708.645	3663.409

Data source: Thomson Reuters Datastream.

Note: AIC = Akaike information criterion, SIC = Schwarz information criterion, ML = value of the maximized likelihood function.

The estimation output for the whole sample period is presented in Table 2. The upper panel of the table presents the coefficient estimates of the mean equations, whereas the second panel shows the variance equation estimates for the different entities. The corresponding ML, AIC and SIC values can be found in Table 1. The  $\omega$  values in the mean equations are all nearly zero, but it is obvious that the coefficient estimates for  $\omega$  and  $\phi$  are often insignificant which is not unusual in the empirical literature though. In fact, the estimation output of the mean equations is often neglected. However, the main focus of the analysis is on the variance estimations which overall show highly significant estimates for the variance and covariance coefficients.

The estimated parameters of the means in the variance and covariance equations ( $c$ ) do not differ substantially from zero. The estimates for the different variance equations proved to be statistically significant at the 1% level, whereas the  $c$  values in the conditional covariances are often insignificant. Exceptions are the covariance between CDS spread changes and stock returns ( $c_{12}$ ) of Bear Stearns, Goldman Sachs and Merrill Lynch. Significant values are also obtained for the covariance between stock returns and bond spread changes ( $c_{13}$ ) of Merrill Lynch and the covariance between CDS and bond spread changes ( $c_{23}$ ) of Goldman Sachs. The coefficients  $b_{ii}$  capture the influence of lagged values of the conditional variances  $h_{ii}$  on the conditional variance today. Accordingly, the larger the coefficient  $b_{ii}$ , the longer is the effect of the shocks (Kirchgässner, Wolters 2007, p. 255). Moreover, high values of  $b_{ii}$

capture the volatility clustering. In other words, high values of  $h_{t-1}$  will be followed by high values of  $h_t$ .

**Table 2: Estimation results of the diagonal BEKK(1,1) model**

	<b>Bear Stearns</b>	<b>Citigroup</b>	<b>Goldman Sachs</b>	<b>Merrill Lynch</b>
$(\omega_{st})$	0.001* (1.631)	0.000 (0.640)	0.002*** (2.787)	0.001 (1.594)
$(\varphi_{st})$	0.006 (0.138)	-0.024 (-0.889)	-0.102*** (-3.850)	-0.068** (-2.117)
$(\omega_{cds})$	0.001 (0.305)	-0.001 (-0.656)	-0.001 (-0.809)	0.000 (-0.146)
$(\varphi_{cds})$	-0.004 (-0.115)	0.003 (0.130)	0.036 (1.327)	0.031 (1.003)
$(\omega_{bo})$	0.003 (0.503)	0.004* (1.644)	-0.001 (-0.546)	0.006* (1.865)
$(\varphi_{bo})$	-0.260*** (-5.814)	-0.291*** (-9.049)	-0.257*** (-7.349)	-0.233*** (-7.497)
$c_{11}$	0.000*** (6.501)	0.000*** (3.618)	0.000*** (5.396)	0.000*** (2.781)
$c_{12}$	0.000*** (-2.633)	0.000 (-0.167)	0.000*** (-3.326)	0.000** (-1.992)
$c_{13}$	0.000 (1.136)	0.000 (0.539)	0.000 (0.256)	0.000*** (2.587)
$c_{22}$	0.000*** (4.868)	0.000*** (10.493)	0.000*** (9.112)	0.000*** (7.619)
$c_{23}$	0.000 (0.021)	0.000 (-0.488)	0.000*** (0.618)	0.000 (-0.536)
$c_{33}$	0.002*** (3.465)	0.002*** (5.623)	0.001*** (11.304)	0.000*** (5.663)
$a_{11}$	0.940*** (49.275)	0.317*** (22.208)	0.223*** (19.434)	0.277*** (13.830)
$a_{22}$	0.358*** (23.105)	0.298*** (25.784)	0.300*** (26.987)	0.344*** (19.918)
$a_{33}$	0.162*** (6.106)	0.295*** (8.128)	0.632*** (41.706)	0.297*** (21.284)
$b_{11}$	0.640*** (32.584)	0.953*** (266.620)	0.972*** (389.427)	0.964*** (170.947)
$b_{22}$	0.935*** (158.126)	0.944*** (326.331)	0.942*** (279.098)	0.928*** (141.833)
$b_{33}$	0.938*** (51.591)	0.805*** (21.579)	0.846*** (162.082)	0.957*** (243.447)
<b>Nobs</b>	629	1043	1043	782

Note: \*\*\*, \*\*, \* indicate significance at the 1%, 5% and 10% level. Z-statistics are in parenthesis. Nobs are number of observations. 1 = st, 2 = cds, 3 = bo.

The estimated coefficients for  $b_{ii}$  are all higher than 0.90 for all three variables across the examined institutions. Exceptions are the bond market coefficients for Goldman Sachs and Citigroup where  $b_{33}$  only exceeds 0.80 which nevertheless is a high value. Moreover, the conditional variances of the three variables for all institutions are significantly affected by the ARCH parameters  $a_{ii}$  which range from 0.162 to 0.940 but the value is mostly in a range of

approximately 0.22–0.36. The results indicate that news/shocks ( $\varepsilon_{t-1}$ ) in the previous period play a minor role in determining the conditional variances and covariances compared to past own values which describe the influence of older information ( $\varepsilon_{t-2}, \varepsilon_{t-3}$ , etc.).

Only the stock returns of Bear Stearns ( $a$  value of 0.94) and the bond spread changes of Goldman Sachs ( $a$  value of 0.623) have higher values, indicating that the respective variances are driven to a larger extent by the lagged error term. This means that, for instance, stock returns of Bear Stearns are more prone to news/shocks from yesterday. Furthermore, information shocks from two or more periods ago are less relevant. This persistence can also be observed in the conditional covariances  $a_{ii}a_{jj} + b_{ii}b_{jj}$  for  $i = 1 \dots 3$  and  $j = 1 \dots 3$ ,  $i \neq j$ . For example the cross-product of the ARCH coefficients of the covariance between stock returns and CDS spread changes for Citigroup amounts to 0.09 and the cross-product of the GARCH coefficients is 0.90. If this is not the case, the volatility or covariance processes would probably be misspecified (Baur 2006, p. 8). The overall significant results for the covariance equations indicate covariation in shocks.

Considering the magnitude of the coefficient estimates of the matrices  $A$  and  $B$  and keeping the condition for covariance stationarity in mind which states that  $\sum_{k=1}^n (a_{ii,k}^2 + b_{ii,k}^2) < 1$   $\forall i = 1, \dots, N$ , the results indicate that the covariance stationarity condition can often not be met. The sum of the squared ARCH and GARCH terms almost always exceeds one (see Table A 1 in the Appendix). Similar results are obtained by Schreiber et al. (2009, p. 14) who also observe an integrated covariance  $H_t$  for a period including the financial crisis for the variables Euro Stoxx 50, iTraxx Europe and the VStoxx. A (nearly) integrated behavior of volatilities could be the result of structural changes and therefore may reflect other dynamics for volatility (Soriano, Climent 2006, p. 46f.). It has been suggested by, for instance, Hamilton and Susmel (1994, p. 312ff.) that an almost integrated volatility process may indicate that the true model for volatility is a regime-switching model (Soriano, Climent 2006, p. 47ff.).

Figure 2 displays the estimated conditional correlations between the stock returns and CDS spread changes, stock returns and bond spread changes as well as CDS and bond spread changes for Citigroup and Goldman Sachs.<sup>8</sup> The first obvious aspect is the strong time

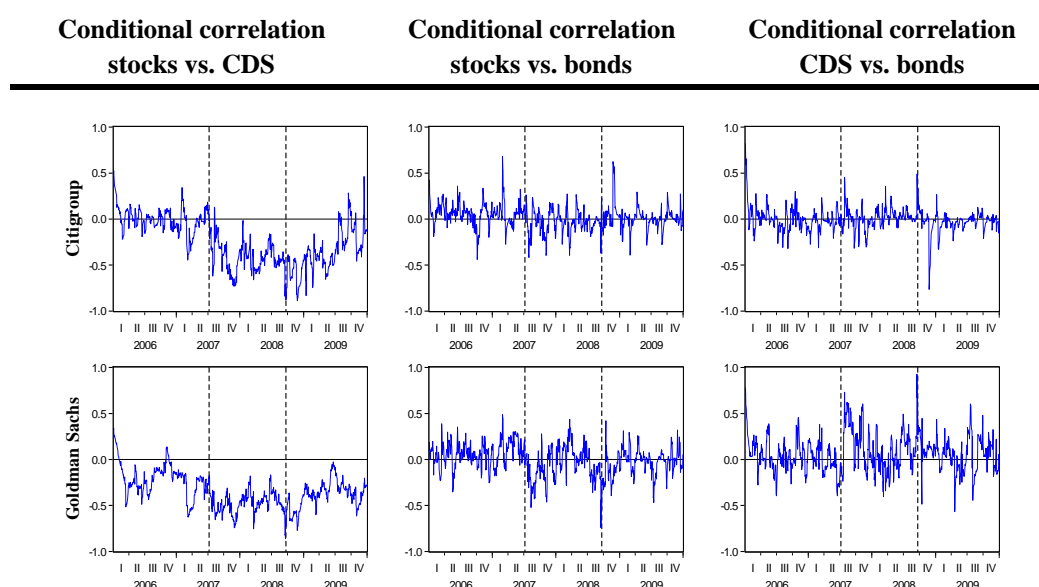
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<sup>8</sup> For the sake of brevity, the figures are only reported for Citigroup and Goldman Sachs. Moreover, the data of both institutions cover the whole sample period and thus allows for a better comparison. The results for Bear Stearns and Merrill Lynch can be found in the Appendix (Figure A 1). They will be only reported in the text if they differ significantly from the results of Citigroup and Goldman Sachs.

variation of all correlations. The apparent structural break in Figure 1 due to the outbreak of the subprime crisis in mid-2007 is also visible in the conditional correlations (cf. dotted vertical line at 6/30/2007). A second strong movement in the conditional correlations can be observed around 9/15/2008 (Lehman Brothers, second dotted vertical line).

The correlations between CDS spread changes and stock returns became more negative after the first break. This can also be observed at the date of the Lehman Brothers failure. These results are quite intuitive, as they imply that falling stock returns tend to be followed by increasing CDS spread changes (CDS spreads widen) and vice versa. This pattern is also reported by Scheicher (2009, p. 415f.) and (Schreiber et al. 2009, p. 14).

**Figure 2: Selected conditional correlations**



Data source: Thomson Reuters Datastream.

Note: Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers), respectively.

The conditional correlations between bond yield spread changes and stock returns show that a former more or less positive conditional correlation turned negative with the outbreak of the crisis and after a reversion again around the Lehman collapse in September 2008. At least during the crisis the negative relation between bond spread changes and stock returns holds. The conditional correlations for Bear Stearns and Merrill Lynch are overall positive for stock returns and bond yield spreads (cf. Figure A 1). The positive correlations might be explained by firm-specific factors. More volatile firm profits affect bond and equity holders differently due to its impact on the likelihood of default. A higher volatility of profits would drive down bond prices (spreads increase) and potentially increase stock prices at the expense of bond

holders. Takeover risk is another factor which potentially influences the relation between stock returns and bond yield spreads (Bhanot, Sattar, Wald 2009, p. 5).

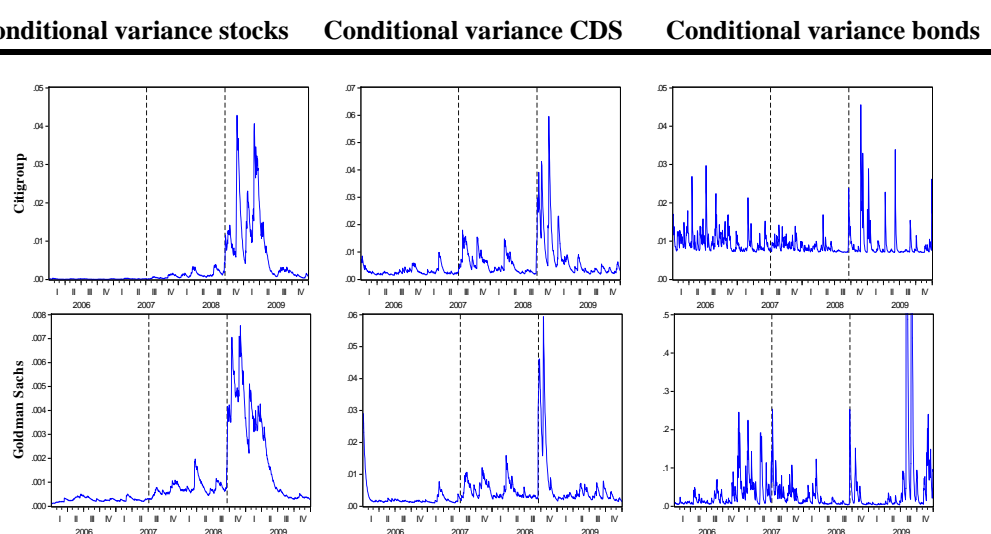
The conditional correlations between CDS and bond spread changes are also highly fluctuating with more or less strong increases at the specific dates (except for Bear Stearns). The positive correlation especially at the start of the crisis and before September 2008 implies that at least around these events increasing CDS spreads tend to be followed by increasing bond yield spreads or vice versa. In other words, both spreads widen, especially when the economic outlook is bad, indicating that market participants expect higher risk in the examined banks.

The movements in conditional correlations suggest that the three variables are interconnected. In particular, since the start of the crisis the correlations increased in absolute terms. This is also true for the conditional correlations between the different variables of Merrill Lynch and partly true for Bear Stearns. This might be explained by the severe problems Bear Stearns was confronted with after they announced the suspension of payments of a large hedge fund in summer 2007 and the early adjustment of the creditworthiness by market participants.

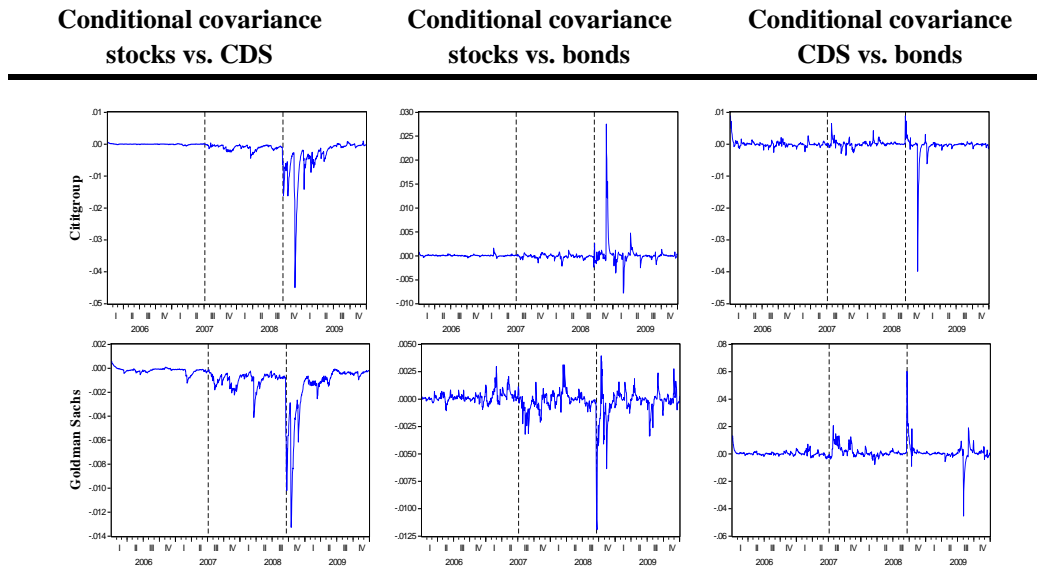
Figure 3 depicts the conditional variances and covariances of the stock returns as well as CDS and bond spread changes for Citigroup and Goldman Sachs. The figures for Bear Stearns and Merrill Lynch can be found in Figure A 2 in the Appendix.

### Figure 3: Selected conditional variances and covariances

#### Panel A: Conditional variances



## Panel B: Conditional covariances



Data Source: Thomson Reuters Datastream.

Note: Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers), respectively.

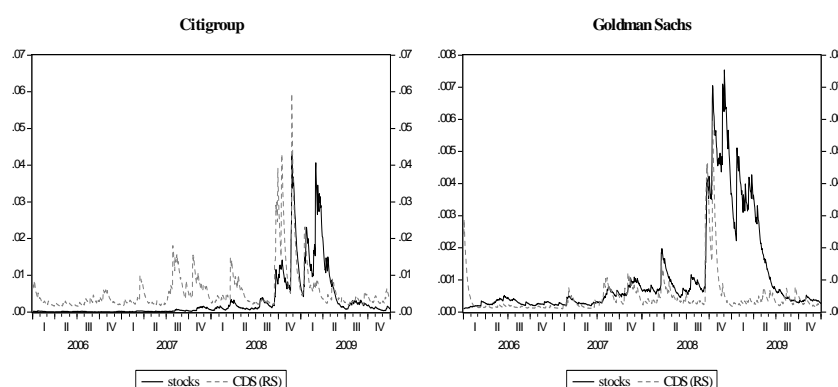
All variances and covariances vary strongly over time and a break in the series can be observed in mid-2007 (approximate start of the subprime crisis) and in particular in September 2008 (collapse of Lehman Brothers). After the outbreak of the crisis, the variations in the variances and covariances are more pronounced and are overall on a higher level. They reach their maximum after the Lehman Brothers' failure which point to the huge impact of this event.

Moreover, the covariances tend to be higher (lower) in times of high (low) volatility. These results are consistent with Schreiber et al. (2009, p. 20) for CDS spreads and stocks, and de Goeij and Marquering (2002, p. 21) for stock and bond returns. If the time-variation in covariances is only due to variation in the variances, the conditional correlations have to be zero. However, considering the estimated correlations in Figure 2, it is obvious that these are not constant over time, indicating that the variability in covariances is not only due to changes in variances (de Goeij, Marquering 2002, p. 22f.).

Especially the variances of the stock returns and credit default swap changes of the different institutions show a clear pattern during the crisis period. Before the failure of Lehman Brothers, three peaks in the CDS variances can be observed, coinciding with certain events which had a huge impact on financial markets. The first peak can be attributed to the liquidation of two Bear Stearns hedge funds that invested in various types of mortgage-backed securities on July 31, 2007. Since mid October 2007 financial market pressure

intensified after the announcement of Citigroup, Bank of America and JPMorgan Chase that they planned to purchase highly rated assets from existing special purpose vehicles and the Fed announced to reduce the target rate. Moreover, at the start of November 2007, liquidity in the interbank funding market dried up which may contribute to the second peak in the (co)variances. The third peak before the Lehman Brothers failure approximately on 14 March, 2008 coincides with the announcement of JP Morgan to purchase Bear Stearns (Fed of St. Louis 2010, p. 3). Those events are also visible in the stock return variances but not as pronounced. Furthermore, after Lehman Brothers, the variances of the stock returns remained on a very high level until mid-2009, whereas the volatility of the CDS spread changes decreased relatively quickly. Accordingly, the stock markets were very anxious at that time and did not expect the turbulence to come to an end for an extended period (this pattern is depicted in Figure 4 and Figure A 3, respectively).

**Figure 4: Comparison of selected stock and CDS variances**



Data source: Thomson Reuters Datastream.

Note: The stock variance is denoted on the left scale; the CDS variance can be read off the right scale (RS).

Although the variances in the bond spread changes do also exhibit the peaks to some extent, they are not as clear-cut as in the other series. It seems that they are determined by other factors as well. This can be seen, for instance, by the jump in the variances at the end of 2009 and the comparably high volatility before the start of the crisis that is not present in the variances of stock returns or CDS spread changes.

The covariances between stock returns and CDS spreads become significantly negative during the crisis with particularly large values in September 2008 and the already observed peaks around the above mentioned dates. This suggests that higher values of the CDS spread changes tend to be paired with lower values of stock returns and that the dependency became stronger at the economically important events. This pattern is partly obvious in the covariance between stock returns and bond spread changes, but again, different forces seem to influence

the series. The covariances between CDS and bond spread changes became more positive around the events but generally, a clear pattern cannot be identified (sometimes large negative values). Around the bankruptcy of Lehman Brothers, all variances and covariances jumped dramatically across all institutions and sometimes reverting former relations (e.g. the high positive values in the covariance of stocks and bonds) emphasizing the huge impact of this event on the financial markets. Overall, the graphical inspection of the covariances and variances implies that major shocks in the financial sector as a whole can be detected in the increasing values across all investigated institutions. Nevertheless, it is hard from the analysis above to make any proposition about the soundness of a single entity, since it is not an easy task to differ between idiosyncratic shocks and common financial market-related shocks.

To summarize, the results for the whole sample period strongly support hypothesis *H1* that all (co)variances and correlations are strongly varying over time with higher levels after the start of the crisis. In addition, hypothesis *H2* can be corroborated for the most part. Variances of CDS spread changes and stock returns reacted similar to shocks occurring in financial markets, whereas the bond spread changes might be influenced by other factors as well. This is also true for the covariances including bond spread changes. The bad performance of bond spread changes could also be explained by the already mentioned factors that influence those spreads. A drawback is the often rejected covariance stationarity condition of the volatility processes and the often insignificant parameter estimates of the mean in the covariance equations. Dividing the whole sample in two sub-periods gives further support for hypothesis *H1*. That means variances and covariances increased during the crisis period. The higher coefficients of the ARCH terms in the crisis period compared to the pre-crisis period suggest that new shocks to the markets exert a higher influence on the conditional (co)variances. Striking exceptions are the bond yield spreads.<sup>9</sup>

#### **5.4 Correlations within the CDS market**

During times of crisis it is a well-documented phenomenon that asset returns become more correlated. This increased co-movement might be explained by a higher correlation in the fundamental values. In the case of CDS, these fundamentals can be, for instance, the components of the Merton model. However, to define fundamentals properly is a point of debate in any market. An alternative explanation of the increased co-movement is contagion (Anderson 2010, p. 1). Contagion effects are important, since they do generally imply positive default correlations (Jorion, Zhang 2007, p. 862).

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<sup>9</sup> Estimation results for the pre-crisis and crisis period are available on request.



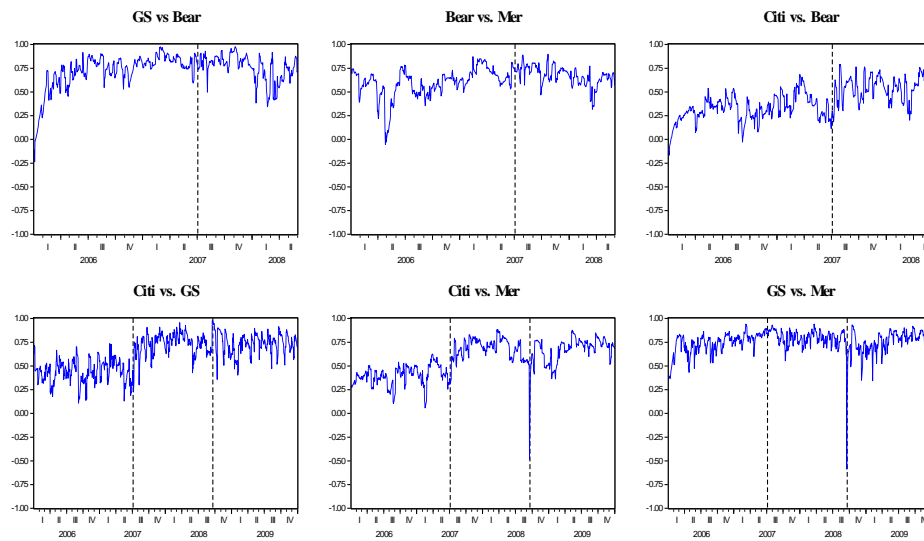
In this section CDS spreads receive special attention in order to assess the dependence structure between the financial institutions' CDS spreads. CDS spreads often perform better in the measurement of borrowers' creditworthiness as bonds, since they are not affected by tax or liquidity effects. Additionally, they could serve as the market's perception of credit risk (Rahman 2009, p. 4f.). Reasons for a joint occurrence of credit events or a deterioration of credit quality of different entities can be cyclical shocks, market-wide adverse factors or close linkages. The close linkage between institutions is often referred to as contagion and is favorable to an increased dependence structure (Rahman 2009, p. 7). Therefore, it would be interesting to see, how the credit default swap spreads of the different institutions have evolved over the whole period, as rising correlations are often considered as the key determinant of contagion (Coudert, Gex 2008, p. 9). Coudert and Gex (2008, p. 41) show that the correlation within the CDS market increases during crisis periods and they state that this could be a hint of contagion. Especially in the banking sector, it is assumed that large institutions are highly connected.

Figure 5 illustrates the estimated conditional correlations between all entities obtained from a bivariate diagonal BEKK(1,1) model. The estimation was also conducted with an AR(1) term in the mean equation to account for the autocorrelation in the series.<sup>10</sup> It is obvious from Figure 5 that the conditional correlations between the CDS spreads of the investigated institutions are overall on a rather high level and are strongly time-varying. The time period for the estimations with CDS spread changes from Bear Stearns only includes observations from 1/1/2006 until 5/30/2008. The conditional correlations between Bear Stearns and Goldman Sachs as well as Bear Stearns and Merrill Lynch do only show a slight increase in correlations around the approximate start of the subprime crisis. This may be due to the already existing very high correlations between those institutions which fluctuate mostly in a range between 0.5 and 1. The same is true for the conditional correlations between Goldman Sachs and Merrill Lynch. This implies that those banks are already highly interconnected with regard to credit default swaps even before the start of the financial crisis.

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<sup>10</sup> The detailed estimation results are available on request.

**Figure 5: Conditional correlations between the institutions' CDS spreads**



Data source: Thomson Reuters Datastream.

Note: Conditional correlations between Bear Stearns and the other institutions end at May 31, 2008. Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers), respectively. Bear = Bear Stearns, Citi = Citigroup, GS = Goldman Sachs, Mer = Merrill Lynch.

A shift around mid-2007 is visible in the conditional correlations of Citigroup and Goldman Sachs, Citigroup and Merrill Lynch, and Citigroup and Bear Stearns. The correlations were higher after the outbreak of the crisis (approximately 0.25 points higher), indicating that the crisis had a perceptible impact on the relation between CDS spread changes of different banks. Another unusual movement can be observed in mid-September 2008, when the conditional correlations between Citigroup and Merrill Lynch, and Goldman Sachs and Merrill Lynch became negative for a short period of time only to jump back on an even higher level afterwards. This again points to the huge distorting impact of the collapse of Lehman Brothers.

All in all, a clear cut in the conditional correlations is visible around mid-2007 with increasing correlations afterwards which confirm hypothesis *H3*. Given the importance of the analyzed institutions, it seems that investors reassessed the risks attached to all borrowers. These results support findings by Coudert and Gex (2008, p. 27f.) who find increased correlations between CDS spread changes during the GM and Ford crisis in 2005 and results obtained by Anderson (2010, p. 32) for the recent financial crisis. Both studies attribute this development to contagion effects. It is not possible from the analysis above to make a statement if fundamental factors potentially play a role in the increased correlations. Nevertheless, it seems very reasonable to conclude from Figure 5 and the findings obtained by the other studies that contagion effects are the drivers of the increased correlations. The understanding

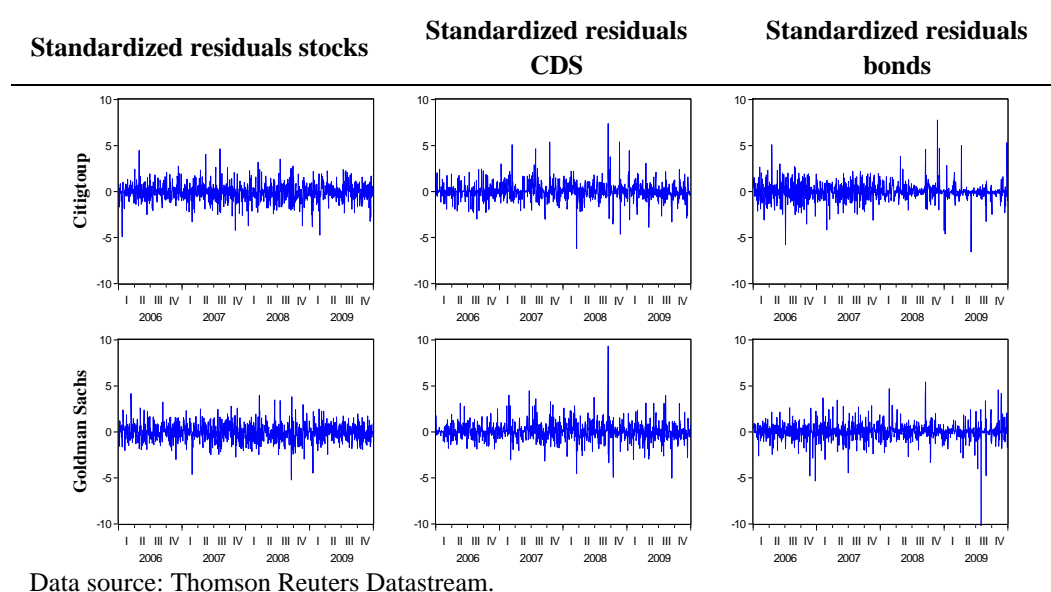
of the dynamics in the CDS market has important implications for supervisory authorities and risk management practitioners (Rahman 2009, p. 14).

### 5.5 Diagnostic testing

After fitting the diagonal BEKK(1,1) model to the data, the appropriateness can be evaluated using a number of graphical and statistical diagnostics on the standardized residuals (Zivot 2009, p.126). Figure 6 presents the standardized residuals of Citigroup and Goldman Sachs which clearly shows that much of the volatility pattern in the original return series can be captured by the diagonal BEKK(1,1) model, although some outliers are still present.

Particularly in the CDS and bond spread changes, the impact of the Lehman Brothers failure is still obvious indicated by large outliers. Overall, the graphical inspection suggests that the diagonal BEKK model was able to capture a significant part of the volatility structure of the data set (Schreiber et al. 2009, p. 15). The figures of the standardized residuals of Bear Stearns and Merrill Lynch can be found in Figure A 4. They show a very similar pattern to those of Citigroup and Goldman Sachs.

**Figure 6: Selected standardized residuals**



The Ljung-Box test statistic of remaining autocorrelation in the standardized and squared standardized residuals corroborates the visual inspection. The results are presented in Table 3, indicating that the null hypothesis of no autocorrelation cannot be rejected for most of the series. Overall, the fit of the model seems to be appropriate.

**Table 3: Ljung-Box statistics for standardized and squared standardized residuals**

	Bear Stearns			Citigroup			Goldman Sachs			Merrill Lynch		
	Stock	CDS	Bond	Stock	CDS	Bond	Stock	CDS	Bond	Stock	CDS	Bond
LB(4)	0.8	13.0**	3.5	4.5	3.0	14.1***	6.7	2.5	18.6***	6.1	4.7	14.6***
LB(12)	19.4*	19.3*	14.9	10.6	9.7	27.7***	10.9	7.6	33.4***	21.3*	12.1	21.0*
LB <sup>2</sup> (4)	5.8	1.2	0.4	8.2*	6.5	0.1	58.5***	12.4**	2.2	27.0***	7.1	0.9
LB <sup>2</sup> (12)	34.3***	79.6***	3.8	10.4	10.4	7.8	62.0***	13.6	5.5	32.7***	9.2	1.6

Data source: Thomson Reuters Datastream.

Note: \*\*\*, \*\*, \* indicate significance levels at 1%, 5% and 10%, respectively. Ljung-Box test of autocorrelation up to lag 36. The numbers in parenthesis stand for the respective lags. LB<sup>2</sup> is the test applied to squared standardized residuals.

All in all, the graphical inspection and the results of the Ljung-Box statistic suggest that the applied multivariate AR(1)-GARCH(1,1) captures the structure in the second order moments of the time series pretty well, but was not able to capture all outliers and remaining autocorrelation. Applying the Jarque-Bera test for normality to the standardized residuals, the null hypothesis of normality must be rejected for all standardized residuals due to the still remaining high kurtosis (see Table A 3 in the Appendix). All tests conducted for the whole sample period have also been applied to the bivariate GARCH in section 5.4. The results can be found in the Appendix (see Tables A 2, A 3 and Figure A 5). Overall, it can be concluded that the diagonal BEKK(1,1) model is able to capture most of the noise in the original series for the considered specifications.

The empirical analysis provides evidence on the time variation in the variances and covariances of all variables and across all institutions. This could have implications for portfolio selection, asset pricing and risk management models (Schreiber et al. 2009, p. 20) which make use of the (co)variation of variables. The same holds for the conditional correlations.

But more importantly, as the variables under consideration represent a measure of bank's risk, a uniform reaction of the institutions risk indicators following a common market shock implies that the bank is confronted with mounting financial problems (Calice, Ioannidis 2009, p. 16). This co-movement could also be observed in the second moments of all three variables, in particular in the stock and CDS series (cf. Figure 3 and Figure 4). For instance, if market participants get concerned about the future performance of a bank, they start to buy CDS contracts as an insurance against a possible default. In doing so, CDS spreads as well as the volatility will rise due to the more active trading (Meng, ap Gwilym, Varas 2009, p. 37). A similar reasoning can be applied to stock returns. Therefore, monitoring the volatility additionally provides useful information with regard to risks in banking sector. Particularly during the very turbulent crisis period the volatility seems to be mainly driven by events with

a huge impact on the financial market as a whole. This can be seen by the simultaneous increase in the (co)variances of all variables and across all institutions.

## **6. Conclusions**

Stock returns, CDS spreads and bond spreads are regarded as an appropriate market-based alternative for credit rating agencies to detect risk in banks timelier and in a more reliable fashion. Employing a multivariate GARCH approach, we have examined the volatility patterns of the former variables. This econometric framework allows us to model the stylized features of financial time series and additionally accounts for the dependency structure between them. For this purpose, we have investigated a data set of four large US banks over the period ranging from January 1, 2006, to December 31, 2009.

The obtained findings support the view that volatility turns out to take higher levels in times of crisis. This is particularly evident in the variances of stock returns and CDS spread changes. Furthermore, correlations and covariances are time-varying and also increased in absolute values after the outbreak of the crisis, indicating stronger dependency of the examined variables. Specific events which have a huge impact on the financial markets as a whole (e.g. the collapse of Lehman Brothers) are also visible in the (co)variances and correlations by means of strong movements in the respective series. This pattern suggests that common factors drive the volatilities of the market-implied indicators. Certain events can also be observed in the (co)variances of bond spread changes. But the latter time series seem to be influenced by other factors as well. The results of our comparative analysis of the pre-crisis and the crisis period clearly reveal that the volatilities during the crisis period have been driven to a larger extent by new shocks hitting the markets. Moreover, our investigation of the CDS spread changes of the different banks delivers evidence of increased correlations during the crisis period which is indicative of contagion effects.

Overall, it appears thus that the multivariate GARCH framework fits the data reasonably well. Nevertheless, in order to capture the dynamics during the very turbulent crisis period and the obvious structural breaks in the (co)variance series, there is some scope to adopt, for instance, a (multivariate) Markov-switching GARCH model.

The soundness of banks is a crucial factor for financial stability as a prerequisite for economic growth. Our volatility analysis sheds light on the development of the (co)variances of prominent market-implied risk indicators, particularly during the financial crisis. The latter appear to be predominantly driven by common market shocks. Although accurately predicting

a bank's failure remains a challenging task, we have shown that analyzing the volatility patterns of CDS spreads, bond spreads and stock prices gives valuable insights for supervising authorities and central banks when evaluating possible financial risks.

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## Appendix

**Table A 1: Covariance stationarity**

	Bear Stearns	Citigroup	Goldman Sachs	Merrill Lynch
Stock	1.29	1.01	0.99	1.01
CDS	1.00	0.98	0.98	0.98
Bond	0.91	0.74	1.11	1.00

Data source: Thomson Reuters Datastream.

**Table A 2: Ljung-Box statistics for standardized and squared standardized residuals, Specification for correlations within the CDS market**

	Bear(1) vs. Mer(2)		Citi(1) vs. Bear(2)		Citi(1) vs. GS(2)		Citi(1) vs. Mer(2)		GS(1) vs. Bear(2)		GS(1) vs. Mer(2)	
	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2
LB(4)	3.0	6.6	1.6	9.0*	4.0	7.7*	4.9	7.9	2.8	1.4	5.2	14.1***
LB(12)	9.5	29.3***	19.4*	14.6	7.3	10.3	9.2	13.8	12.3	10.8	8.8	23.5**
LB <sup>2</sup> (4)	1.1	4.4	1.1	1.0	3.1	3.8	10.5**	12.8***	1.1	3.9	2.1	3.3
LB <sup>2</sup> (12)	18.0	8.9	4.9	15.0	5.1	5.2	12.4	16.2	2.8	42.2***	2.4	6.8

Data source: Thomson Reuters Datastream.

Note: \*\*\*, \*\*, \* indicate significance levels at 1%, 5% and 10% respectively. Ljung-Box test of autocorrelation up to lag 36. The numbers in parenthesis stand for the respective lags. LB<sup>2</sup> is the test applied to squared standardized residuals. *sr* = standardized residual. Numbers in parentheses after the banks' name correspond to the respective *sr* numbers.

**Table A 3: Jarque-Bera test for standardized residuals**

Panel A: Basic specification

	Bear Stearns			Citigroup			Goldman Sachs			Merrill Lynch		
	<i>sr</i> st	<i>sr</i> cds	<i>sr</i> bo	<i>sr</i> st	<i>sr</i> cds	<i>sr</i> bo	<i>sr</i> st	<i>sr</i>	<i>sr</i> bo	<i>sr</i> st	<i>sr</i>	<i>sr</i> bo
J-B	4735.8	1771.4	65108.7	291.9	2875.3	4274.3	216.7	4026.3	13332.2	53.4	602.4	8814.6
Prob.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

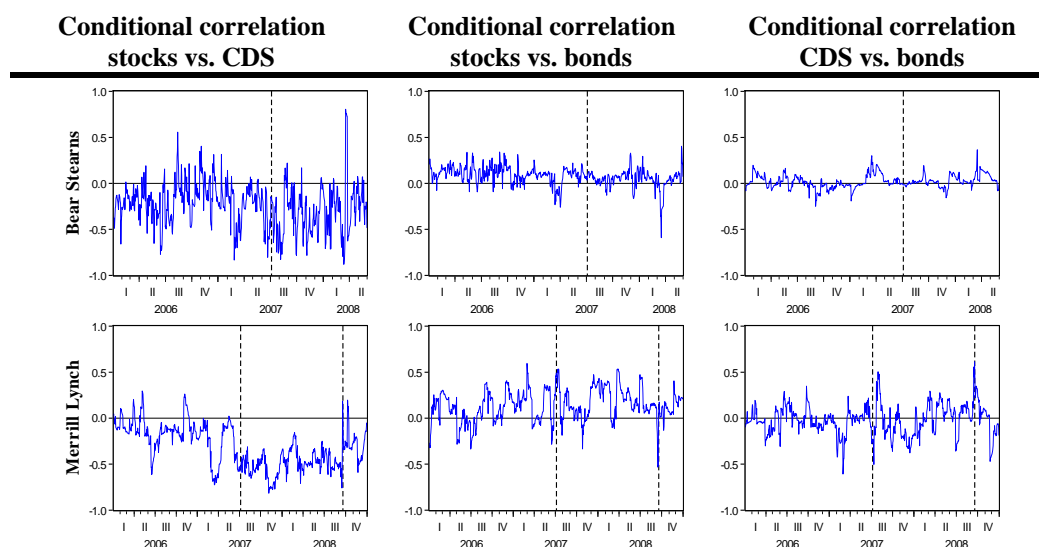
Panel B: Specification for correlations within the CDS market

	Bear(1) vs. Mer(2)		Citi(1) vs. Bear(2)		Citi(1) vs. GS(2)		Citi(1) vs. Mer(2)		GS(1) vs. Bear(2)		GS(1) vs. Mer(2)	
	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2	<i>sr</i> 1	<i>sr</i> 2
J-B	953.6	572.3	1277.5	748.0	3639.6	1565.6	10393.8	1367.4	327.1	818.7	84392.1	1603.8
Prob.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Data source: Thomson Reuters Datastream.

Note: Null hypothesis of the Jarque-Bera test states that the series is normally distributed. High J-B values and low Prob. values indicate that the null hypothesis have to be rejected. *sr* = standardized residual. Numbers in parentheses after the banks' name correspond to the respective *sr* numbers.

**Figure A 1: Conditional correlations for Bear Stearns and Merrill Lynch**

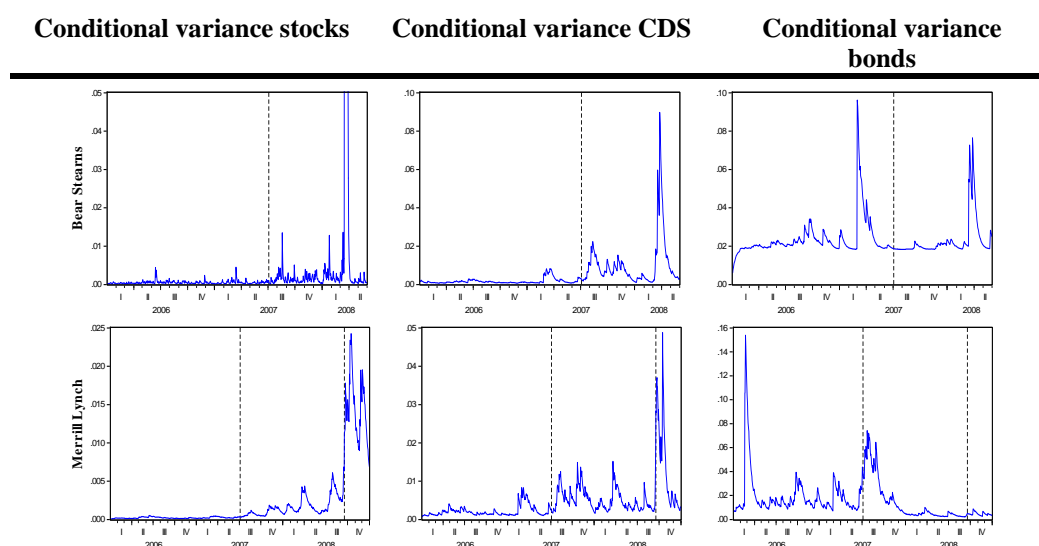


Data source: Thomson Reuters Datastream.

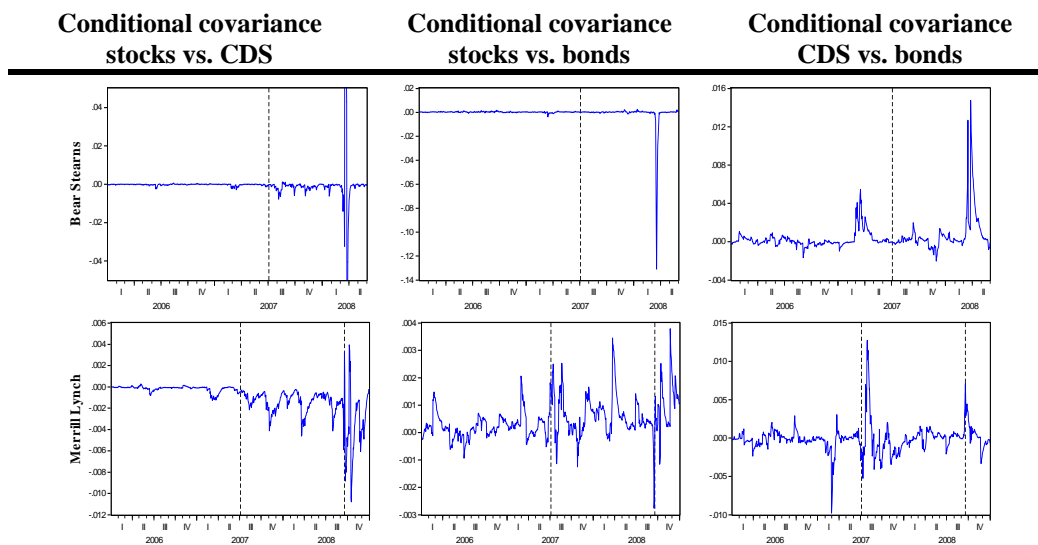
Note: Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers).

**Figure A 2: Conditional variances and covariances for Bear Stearns and Merrill Lynch**

Panel A: Conditional variances



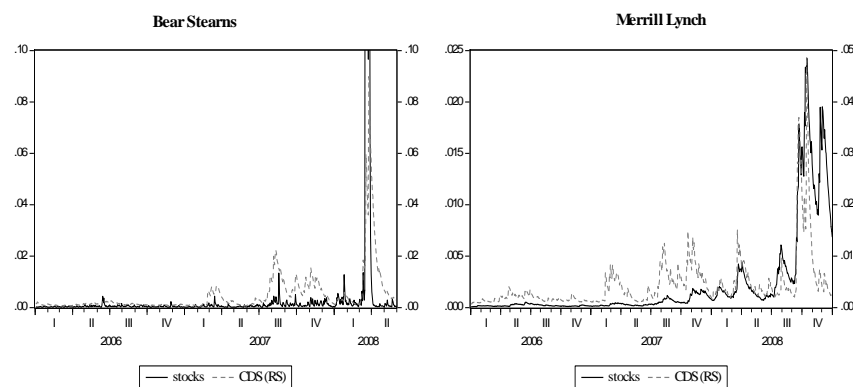
## Panel B: Conditional covariances



Data source: Thomson Reuters Datastream.

Note: The variances and covariances of Bear Stearns end at 5/31/2008, for Merrill Lynch at 12/31/2008. Dotted vertical lines refer to 6/30/2007 (approximate start of the crisis) and to 9/15/2008 (failure of Lehman Brothers).

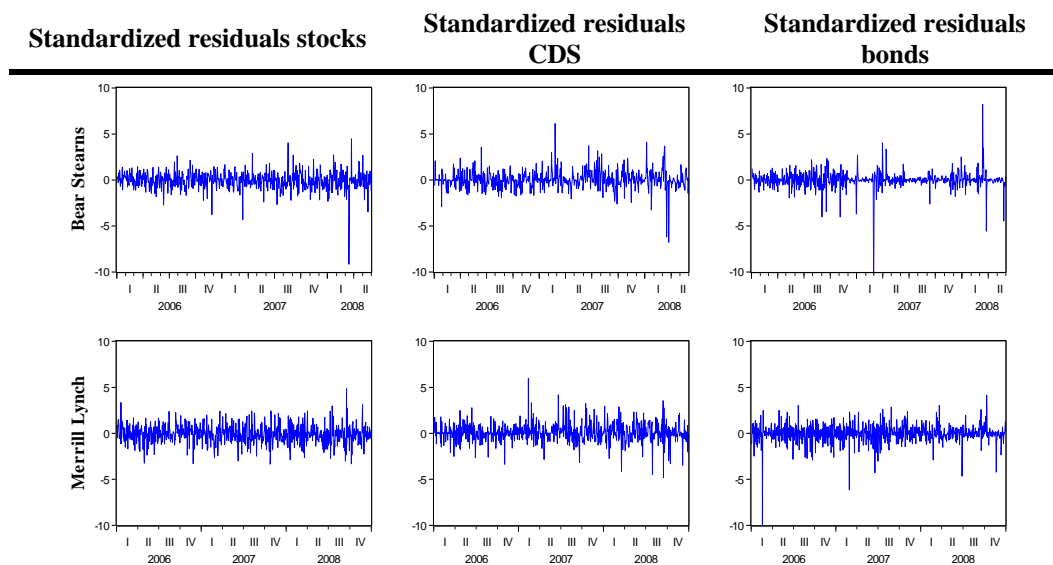
**Figure A 3: Comparison of stock and CDS variances for Bear Stearns and Merrill Lynch**



Data source: Thomson Reuters Datastream.

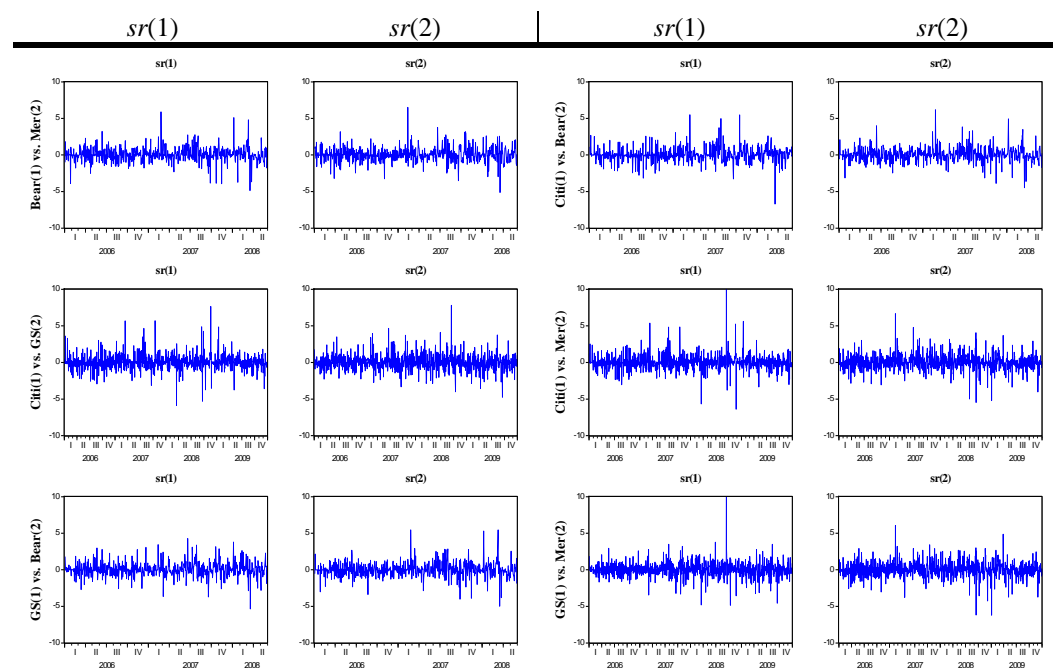
Note: The stock variance is displayed on the left scale and the CDS variance on the right scale (RS).

**Figure A 4: Standardized residuals of Bear Stearns and Merrill Lynch**



Data source: Thomson Reuters Datastream.

**Figure A 5: Standardized residuals, Specification for correlations within the CDS market**



Data source: Thomson Reuters Datastream.

Note:  $sr$  = standardized residual. Numbers in parentheses after the banks' name correspond to the respective  $sr$  numbers.